Heat Exposure and Youth Migration in Central America and the Caribbean

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Emerging evidence demonstrates migration may be used by individuals in the southern hemisphere to adapt to environmental changes (Feng, Kreuger and Oppenheimer, 2010; Marchiori, Maystadt and Schumacher, 2012). Few studies measure the environmental drivers of migration in the Latin America and Caribbean region as a whole. Furthermore, while it is well-documented that the liquidity-constrained often move temporarily or over short distances in response to a localized, negative shock (Fussell, Hunter and Gray, 2014), the permanent migration impact of prolonged or repeated exposure to changes in the environment is poorly understood. First, ambiguities about risk caused by gradual environmental degradation may result in minimal behavioral change (Lee et al., 2015). Second, low-income households may not afford transportation between locations or have sufficient social capital to secure employment in urban areas (Bryan, Chowdhury and Mobarak, 2014) . These features challenge the forced migration rhetoric, instead offering a scenario in which populations are trapped in place (Black et al., 2011).

We build upon recent work in the region using a similar triple difference-in-difference quasi-experimental design and dataset to test whether repeated and/or prolonged heat exposure affect inter-province migration (Baez et al., Forthcoming). We previously illustrated that youth are more likely to move in response to hurricanes and droughts. Exposure to temperature extremes may render greater consequences on the mobility of individuals than natural disasters. Social protection programs often target populations affected by natural disasters reducing their vulnerability but individuals rarely receive social assistance due to the fact of being exposed to a heat wave. In addition, widespread disasters can compromise employment opportunities and inflate transportation costs; both reducing net migration benefits.

The growth literature has pointed to numerous examples in which environmental migration contributes to urbanization (Henderson, Storeygard and Deichmann, 2017) without growth (Poelhekke, 2011). We therefore additionally predict how gradual changes in temperature influence the skill set of who migrates and their location choice. We further confirm using two separate datasets whether the observed mobility patterns correspond with changes in income levels, by examining the GDP losses at the district and national levels. The former may be indicative of local vulnerability, while national vulnerability from prolonged heat exposure can narrow the set of employment opportunities at destinations reducing the desirability of environmental migration.

I. Data

Migration: Migration data are taken from censuses conducted in the following countries (Minnesota Population Center, 2015): Costa Rica (2000, 2011), Dominican Republic (2002, 2010), El Salvador (1992, 2007), Haiti (1982, 2003), Mexico (2000, 2010), Nicaragua (1995, 2005), and Panama (2000, 2010). The information allows for measurement of individual inter-province migration over the five years prior to the census. We create three migration variables

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based on the province destination of each individual, whether the person migrated across provinces, whether the person migrated across provinces to the national capital, and whether the person migrated across provinces to a provincial capital. Individual age, gender, education, and province origin are used to formulate the explanatory variables included in the regressions.[1]

Climate: Daily temperature are extracted from the Global Land Data Assimilation System Version 2 (1983-2010).[2] We focus on heat exposure over the migration period. To formulate a standardized measure of heat exposure, we perform the following steps. First, we create a binary indicator for whether the daily minimum temperature is in the 90th percentile of the province distribution. Second, we create variables reflecting the number of days that the daily minimum temperature exceeds the 90th percentile over moving 5-year averages, starting with 1983 and ending with 2010. Third, we use the distribution (23 points) of the number of "extremely hot" days over periods of 5 years to construct the means and standard deviations of each province distribution.

Next, we use the above data to create a heat exposure z score: the number of days exceeding the 90th percentile (over the 5-year migration period in the census follow-up round), and the means and standard deviations of each origin province distribution. Areas with heat exposure values of zero or below in the follow-up round are considered "unaffected" for the purpose of the experiment. Z score values less than zero are replaced by the value zero. "Affected" areas are defined by provinces having positive z score values, allowing heat exposure to vary in intensity by maintaining the continuous z score values.[3]

Precipitation data are taken from the Climate Research Unit's Time Series of the University of East Anglia (1983-2010). Five-year average precipitation and precipitation squared variables are created to reduce bias from unobserved, correlated weather characteristics in regressions (Auffhammer et al., 2013). All temperature and precipitation variables are then merged by the origin province and survey year of each individual in the censuses.

Gross Domestic Product: To examine whether heat-induced income fluctuations drive migration patterns, we use two sources of Gross Domestic Product (GDP) data adjusted using the purchasing power parity rates in 2011 international dollars. The first source comes from statistical models produced by the World Bank to predict province-level GDP.[4] One shortcoming of the detailed data is its limited spatial (e.g., Costa Rica, El Salvador, Nicaragua, and Panama) and temporal (2000, 2005, 2010) availability. We therefore also exploit the World Development Indicators (WDI) database which concentrates on the national GDP for all seven countries over the timeframe of our censuses (1987-2010).

II. Identification

We evaluate the effect of repeated and prolonged heat exposure on inter-province migration by building on the triple difference-in-difference (DID) design in Baez et al. (Forthcoming). Double difference-in-difference (DID) models are commonly used to identify the impact of shocks on outcomes in the absence of panel data, comparing outcomes before and after exposure in affected and unaffected

[1]Summary statistics of the explanatory variables included in the empirical model can be found in the Appendix.

[2]We use this dataset over others that measure surface temperature as it offers daily (rather than monthly) values at a fine scale of 0.25 × 0.25 degrees.

[3]A figure illustrating the distribution of the heat exposure variable is provided in the Appendix.

[4]The data are part of a project developed under the World Bank Latin America Caribbean Region Probabilistic Risk Assessment Program, CAPRA (P144982), which is funded by the World Bank through a Global Facility for Disaster Reduction and Recovery (GFDRR) grant (TF014499) from the Goverment of Australia (AusAid). The methodology will be available in a World Bank Working Paper in preparation "Growth Domestic Product Disaggregation Methodology and Applications in Disaster Risk Management" by P. Blanchard, B. Blankespoor, J. Rivera-Fuentes, R. Gunasekera, O. Ishizawa, and L. F. Jimenez-Salazar. For more information, please contact O. Ishizawa at oishizawa@worldbank.org.

provinces. One drawback of the double DID approach is it assumes there are no other micro-level shocks in affected areas at the time of exposure. Using the same data, Baez et al. (Forthcoming) exploit an additional dimension, timing of birth, for identification decomposing the sample by high-mobility (ages 15-25, 26-35) and low-mobility (ages 36-45, 46-55, and 56-65) groups. This additional dimension circumvents the bias caused by time variant shocks by further drawing comparisons of the changes in outcomes by heat exposure across age groups.

A linear probability model is used to quantify the effects of heat exposure on the migration of men and women:

$$\begin{aligned} M_{ijkat} = {} & \beta_{\mathbf{1}}(Temp_k \times \mathbf{Age_a} \times After) \\ & + \beta_{\mathbf{2}}(Temp_k \times \mathbf{Age_a}) \\ & + \beta_{\mathbf{3}}(Temp_k \times After) \\ & + \beta_{\mathbf{4}}(\mathbf{Age_a} \times After) + \theta \mathbf{X}_{ijkt} \\ & + \alpha_j + \delta_t + \gamma_a + \epsilon_{ijkat}, \end{aligned} \tag{1}$$

where M_{ijkat} is a binary variable for whether individual i at destination province j from origin province k in age group a at time t migrated in the last five years; $\mathbf{Age}_a$ is a vector of ten-year age indicators (15-25, 26-35, 36-45, 46-55, 56-65 omitted); $After_t$ signifies the follow-up census for the country; X_{ijkt} is a vector of pre-shock variables (indicators for being male and having completed primary school, and five-year average precipitation and precipitation squared at origin). Location, generational and temporal factors that influence migration patterns are controlled for by including origin α_j, age γ_a, and year δ_t fixed effects.[5] Standard errors are clustered by origin province and birth year.

Identification rests on the following assumptions. First, our methodology assumes disasters would affect the migration status of an individual in the 15-35 age range significantly more than individuals outside of that age range (36-65). Difference-in-difference regression results which compare the change in the mobility patterns across age groups confirm that younger men and women are more likely to move and the migration patterns of young men and women are more likely affected in the follow-up censuses (Appendix). Second, we assume differences across birth cohorts in migration rates would be similar across "affected" and "non-affected" districts in the absence of the shock. We validate that the changes in the baseline characteristic averages across age groups and exposure categories are statistically insignificant (Appendix).

III. Results

Table 1 provides the parameter estimates and standard errors from model (1) using the three migration outcomes disaggregated by the gender of the individual. We only observe a positive and statistically significant effect on the migration of women to a provincial capital. The tendency of women to migrate in response to temperature variability is consistent with recent evidence in South America (Thiede, Gray and Mueller, 2016). Women may be used to diversify risk, if the opportunity cost of having an absent young male member of the household exceeds that of a young female member. Alternatively, income losses caused by fluctuations in temperature may affect the demand for goods and services provided by female-dominated industries (e.g. seamstresses).

Table 2 presents the migration impacts of heat exposure among the unskilled (has not completed a primary education).[6] A one standard deviation increase in heat exposure more than doubles (quadruples) the probability of a young (ages 15-25), unskilled woman to migrate to a provincial (national) capital. Restricting the focus to the unskilled also introduces a positive and significant effect on the provincial capital migration of women ages 26-35, and a positive and significant effect on the provincial

[5]Controlling for pull factors through the inclusion of destination province fixed effects does not change inferences on the parameters of interest. We focus on the abbreviated empirical model given concerns over the potential for biased estimates generated from the endogeneity of location decisions.

[6]There are no significant impacts on the skilled sample (Appendix).

Table 1—Impact of Heat Exposure on Migration

Sample	Women			Men		
Destination	Any	National Capital	Provincial Capital	Any	National Capital	Provincial Capital
Temp × After × Age 15-25	-0.00011	-0.00106	0.00300*	-0.00018	0.00012	0.00161
	(0.0058)	(0.00110)	(0.00178)	(0.00562)	(0.00081)	(0.00168)
Temp × After × Age 26-35	0.00282	0.00027	0.00169	0.00053	-0.00003	0.00062
	(0.00654)	(0.00107)	(0.00188)	(0.00704)	(0.00099)	(0.00190)
Temp × After × Age 36-45	0.00193	0.00026	0.00864	0.00008	0.00040	0.00001
	(0.00546)	(0.00009)	(0.00187)	(0.00615)	(0.00083)	(0.00183)
Temp × After × Age 46-55	0.00284	0.00061	0.00069	-0.00074	0.00046	-0.00088
	(0.00590)	(0.00109)	(0.00222)	(0.00649)	(0.00093)	(0.00214)
Constant	-0.00502	-0.01988***	-0.02864***	-0.01062	-0.01573***	-0.02328***
	(0.01321)	(0.00342)	(0.00468)	(0.01421)	(0.00253)	(0.00440)
Mean temp	0.751	0.752	0.749	0.737	0.738	0.735
Mean control migration rate	0.023	0.001	0.008	0.024	0.001	0.008
R-squared	0.073	0.242	0.113	0.061	0.259	0.098
Observations	8,599,759	8,283,727	8,310,807	7,883,317	7,589,007	7,618,804

Note: Temp represents the standardized number of excessive heat days experienced over a five-year period. Origin-province by birth year clustered standard errors in parentheses. *** $p < 0.01$, * $p < 0.1$.

capital migration of young men.

The GDP regressions qualitatively suggest that the observed migration patterns do not coincide with any broad economic losses (Appendix). Young women may be used by households to obtain auxiliary income to smooth consumption. Consequently, they travel to provincial and national capitals because these areas are at least perceived to offer a greater range of employment opportunities given their skills.

IV. Discussion

Our results imply that a 1-standard deviation increase in heat would affect the lives of 7,314 young women[7] and 1,578 young men. The total effect is smaller than that observed under droughts (41,559 people) or hurricanes (13,931 people), but could increase with climate change. In all instances, we are likely to omit a significant fraction of short-distance moves due to data limitations. What is most disconcerting is that youth are more likely to wind up in urban centers when exposed to heat than the common disasters experienced in the region. Additional research is warranted over the welfare implications of these choices in the long term and the interventions available to minimize distress migration.

[7]This calculation comes from multiplying the total number of unskilled workers (2,619,639), the percentage of individuals aged 15-25 (0.35), and the coefficient in Table 2 (0.008).

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Table 2—Heat-Induced Migration Patterns of the Unskilled, Without Primary Education

Sample	Women			Men		
Destination	Any	National Capital	Provincial Capital	Any	National Capital	Provincial Capital
Temp × After × Age 15-25	0.00571	0.00443**	0.00760***	0.00201	0.00111	0.00212*
	(0.00550)	(0.00185)	(0.00201)	(0.00447)	(0.00082)	(0.01263)
Temp × After × Age 26-35	0.00637	0.00109	0.00271**	0.00010	0.00082	0.00012
	(0.00533)	(0.00096)	(0.00141)	(0.00491)	(0.00069)	(0.00121)
Temp × After × Age 36-45	0.00354	0.00160	0.00190	-0.00136	0.00120**	0.00003
	(0.00455)	(0.00098)	(0.00143)	(0.00452)	(0.00058)	(0.00106)
Temp × After × Age 46-55	0.00256	0.00115	0.00062	-0.00027	0.00025	-0.00104
	(0.00463)	(0.00084)	(0.00142)	(0.00444)	(0.00058)	(0.00118)
Constant	0.06011***	0.01794**	0.00935	0.01811	0.00583*	-0.00985*
	(0.01502)	(0.00703)	(0.00849)	(0.01392)	(0.00347)	(0.00570)
Mean temp	0.782	0.784	0.782	0.737	0.739	0.737
Mean control migration rate	0.020	0.001	0.005	0.019	0.001	0.005
R-squared	0.117	0.324	0.212	0.080	0.318	0.145
Observations	2,688,088	2,612,545	2,619,639	2,246,249	2,184,378	2,191,324

Note: Temp represents the standardized number of excessive heat days experienced over a five-year period. Origin-province by birth year clustered standard errors in parentheses. *** $p < 0.01$, * $p < 0.1$.

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Appendix

Table A1—Summary Statistics

Sample	Women		Men	
	Mean	SD	Mean	SD
Urban	0.594	0.491	0.584	0.493
Male	0.000	0.000	1.000	0.000
Migrate	0.044	0.204	0.043	0.203
After	0.566	0.496	0.563	0.496
Age 15-25	0.348	0.476	0.356	0.479
Age 26-35	0.242	0.428	0.233	0.423
Age 36-45	0.191	0.393	0.189	0.391
Age 46-55	0.131	0.338	0.132	0.338
Age 56-65	0.088	0.283	0.090	0.286
Five-year precipitation average	1312.086	652.232	1314.937	663.910
Has primary education	0.687	0.464	0.715	0.451
Lives in provincial capital	0.010	0.101	0.010	0.099
Lives in country capital	0.007	0.084	0.006	0.077
After × Age 15-25	0.190	0.392	0.196	0.397
After × Age 26-35	0.132	0.339	0.126	0.332
After × Age 36-45	0.111	0.314	0.108	0.310
After × Age 46-55	0.080	0.272	0.079	0.270
Temp	0.750	0.593	0.736	0.593
Temp × After × Age 15-25	0.145	0.396	0.148	0.399
Temp × After × Age 26-35	0.100	0.334	0.092	0.321
Temp × After × Age 36-45	0.085	0.311	0.080	0.302
Temp × After × Age 46-55	0.062	0.270	0.060	0.265
Temp × After	0.434	0.586	0.422	0.581
Temp × Age 15-25	0.262	0.501	0.264	0.501
Temp × Age 26-35	0.179	0.430	0.168	0.417
Temp × Age 36-45	0.143	0.392	0.138	0.385
Temp × Age 46-55	0.099	0.334	0.098	0.332
N	8,599,759		7,883,317	

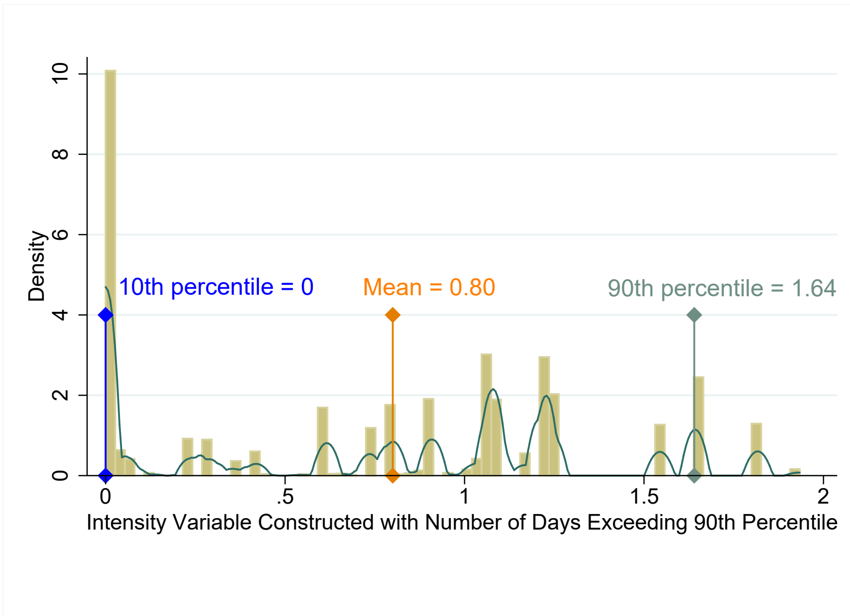

Figure A1. Distribution of Heat Exposure

Table A2—Double-Difference Regression

	Women Parameter (SE)	Men Parameter (SE)
Age 15-25	0.02899***	0.01845***
	(0.00141)	(0.00155)
Age 26-35	0.02631***	0.02714***
	(0.00137)	(0.00136)
Age 36-45	0.00959***	0.01422***
	(0.00116)	(0.00126)
Age 46-55	0.00184	0.00395***
	(0.00116)	(0.00112)
Age 15-25 × After	-0.01033**	-0.00964***
	(0.00187)	(0.00202)
Age 26-35 × After	-0.00333*	-0.00423**
	(0.00172)	(0.00175)
Age 36-45 × After	-0.00003	-0.00189
	(0.00172)	(0.00174)
Age 46-55 × After	-0.00124	-0.00179
	(0.00193)	(0.00190)
Constant	-0.00319	-0.00942
	(0.01356)	(0.01472)
R-squared	0.063	0.052
Observations	8,599,759	7,883,317

Note: The sample used for the regressions include the following seven countries: Costa Rica, Dominican Republic, El Salvador, Haiti, Mexico, Nicaragua and Panama. Covariates include primary education, 5-year average rainfall, 5-year average rainfall squared, year and province origin fixed-effects. Origin province by birth year clustered standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3—Balancing Table for Male Sample

Age Provinces	15-35 Affected	36-65 Affected	Diff.1	15-35 Unaffected	36-65 Unaffected	Diff.2	Diff.1-Diff.2	P-value
Migrate 15-25	0.068	0.050	0.018	0.048	0.036	0.013	0.005	0.926
Primary education	0.820	0.609	0.211	0.795	0.583	0.212	-0.001	0.963
Precipitation	1168.637	1144.389	24.247	1389.310	1419.278	-29.968	54.215	0.487

Note: N=7,883,317. Precipitation=five-year precipitation average. Origin province by birth year clustered standard errors in parentheses.

Table A4—Balancing Table for Female Sample

Age Provinces	15-35 Affected	36-65 Affected	Diff.1	15-35 Unaffected	36-65 Unaffected	Diff.2	Diff.1- Diff.2	P-value
Migrate 15-25	0.073	0.046	0.026	0.051	0.030	0.020	0.006	0.510
Primary education	0.797	0.540	0.257	0.806	0.533	0.273	-0.016	0.515
Precipitation	1179.222	1141.894	37.328	1362.077	1396.440	-34.362	71.690	0.390

Note: N=8,599,759. Precipitation=five-year precipitation average. Origin province by birth year clustered standard errors in parentheses.

Table A5—Heat-Induced Migration Patterns of the Skilled

Sample estination	Any	Women National Capital	Provincial Capital	Any	Men National Capital	Provincial Capital
Temp × After × Age 15-25	-0.00341	-8.54e-05	0.00219	-0.00344	0.00128	0.00154
	(0.00714)	(0.00133)	(0.00267)	(0.00691)	(0.00109)	(0.00240)
Temp × After × Age 26-35	-0.000726	0.00178	0.00155	-0.00304	0.000928	0.000621
	(0.00792)	(0.00138)	(0.00281)	(0.00838)	(0.00128)	(0.00263)
Temp × After × Age 36-45	-0.000593	0.00129	0.000867	-0.00317	0.00103	-0.000190
	(0.00701)	(0.00128)	(0.00285)	(0.00757)	(0.00117)	(0.00263)
Temp × After × Age 46-55	0.00242	0.00115	0.00111	-0.00357	0.00116	-0.000474
	(0.00812)	(0.00159)	(0.00353)	(0.00851)	(0.00136)	(0.00317)
Constant	-0.0155	-0.0222***	-0.0271***	-0.0128	-0.0171***	-0.0201***
	(0.0155)	(0.00359)	(0.00539)	(0.0168)	(0.00305)	(0.00538)
Mean temp	0.737	0.738	0.734	0.737	0.738	0.735
Mean control migration rate	0.028	0.002	0.011	0.032	0.001	0.011
R-squared	0.06	0.22	0.09	0.06	0.25	0.09
Observations	5,911,671	5,671,182	5,691,381	5,637,068	5,404,629	5,427,480

Note: Same variables included as the specifications in Table 1, except education is omitted. Skilled includes those who have completed their primary education. *** $p < 0.01$, **$p < 0.05$, * $p < 0.1$. Origin province by birth year clustered standard errors in parentheses.

Table A6—Impact of Cumulative Heat Exposure on the Natural Logarithm of GDP

Unit of Analysis	Province	Country
Temp	-0.00957	-0.0263
	(0.0300)	(0.0252)
Constant	4.336***	4.107**
	(0.333)	(1.124)
Observations	123	147

Note: Temp represents the standardized number of excessive heat days experienced over five-year period. GDP is adjusted by PPP in 2011 international dollars and scaled by a billion. All regressions include 5-year average rainfall, 5-year average rainfall squared, province(country), and year fixed effects. Province(country)-clustered standard errors in parentheses. ***$p < 0.01$, ** $p < 0.05$.